Registration of Time-Series Contrast Enhanced Magnetic Resonance Images for Renography

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Abstract

Renovascular disease is an important cause of hypertension. For assessing treatment options for renovascular disease such as angioplasty or nephrectomy, it is important to characterize the renal tissue. Magnetic resonance (MR) renography is becoming a viable method for characterization of the renal tissue. However, analysis of MR renography is hampered by tissue motion. We investigate two automated image registration methods for minimization of the effects of tissue motion The first is semi-automated registration using contours. The second is an adaptation of the Automated Image Registration (AIR) algorithm that accommodates large-scale motion and tissue enhancement from a contrast agent. We compared the results of these methods with manual registration using image overlays. Semi-automated registration using contours accurately registered a 2D MR renography data set of 140 time frames with obvious errors in only 7 slices. With correction in those slices, semi-automatic registration had equivalent quality to manual registration. The adaptation of the AIR algorithm produced better results on 3D MR renography in healthy kidneys than manual registration but worse results in a diseased kidney. We conclude that automated registration of 2D and 3D MR renography is feasible.

1. Background

Registration of time-series images acquired over the course of contrast enhancement, or so-called dynamic MR, is a challenging problem. Typically such images are acquired in tissues where large-scale tissue displacement can exist between images due to variation in inspiration for breath-hold images or, for example, due to stretching of unsupported breast tissue over the course of the exam. Furthermore, the displacement of soft tissue from one time frame to another may be complex, having both rigid and elastic components. Registration of dynamic MR is also challenging because the appearance of the tissue changes markedly over the course of the enhancement. Since the various tissue types do not enhance uniformly, the relative intensities between tissues vary with time.

Several methods have been developed for registration of dynamic MR or dynamic radionuclide imaging. A landmark-based method has been developed for 2D dynamic MR[1]. In this method a contour is drawn around the kidney in one time frame. That contour is then registered to all edge images derived from all other images in the time series. Problems related to variation in image contrast are minimized when using contours and edge images. Our 2D registration method is an extension of this method.

A registration method has also been proposed for analysis of cardiac dynamic MR[2]. In this method, a single mask is manually drawn around the 2D short-axis cross-section of the heart that most nearly approximates the heart shape without excluding the heart from any time frame. The images within the masked region for all time frames are registered to one another. The reference or standard image is the accumulated average of the registered images. The registration was performed by the least-squares criterion. The registration method used a 3-parameter rigid model of motion. Our 3D registration method is an extension of this method.

A registration method has also been developed for mammographic dynamic MR[3]. The cost function in this method is the mutual information. Mutual information is a measure of similarity between images that is insensitive to differences in relative contrast between the images. This method requires only that each individual tissue within the image vary in intensity consistently from one image to another. However, no comparison is made between registration using the mutual information cost-function and, for example, a more conventional least-squares cost function.

The Automated Image Registration (AIR) algorithm[4,5] has been applied extensively to functional brain MR. In that application, motion between images is important but small-scale. The direct application of this algorithm has thus far not been established. We discuss a multiple-step procedure that incorporates the AIR algorithm for registration of dynamic MR of the kidneys.

2. MR Renography

3D MR studies were analyzed for 3 kidneys from 2 subjects. One subject (subject 1) was a normal volunteer; the other was a patient with renovascular disease (subject 2). 3D Fast Time-of-Flight MR images were acquired following intravenous injection of Gd-DTPA contrast agent on a 1.5T system (GE Medical Systems, Milwaukee, WI). Each time frame was acquired during a breathhold. The slices were 5-mm thick. The field-of-view was 40 cm. The image matrix was 128x256. For subject 1, each volume contained 7 images. 27 time frames were acquired. For subject 2, the volume for each time frame contained 12 images and 30 time frames were acquired. A slice at the middle of the volume is shown for several time points in figure 1. For 2D MR renography, images were analyzed for one kidney from a normal volunteer (Subject 3) (Acquired at 1 frame / second).
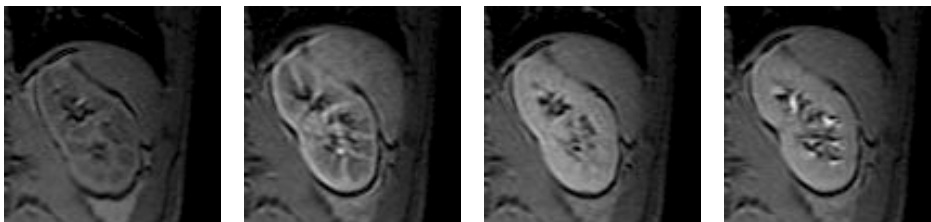

Figure 1. 3D MR Renography. Slice from every 5th time frame of MR renogram.

3. Registration Methods

3.1. Manual Registration

Time-series image slices were manually registered to one another to correct for in-plane translational motion using a utility from the Medical Image Processing, Analysis and Visualization (MIPAV) (Center for Information Technology, National Institutes of Health). MIPAV manual registration is carried out by superimposing two images. One image is registered to a second (standard) image by dragging the image until a maximum "focus" was obtained between the two images. Superimposed images are displayed in real-time. Manual registration was performed on all images throughout the time series. The standard image was updated several times throughout the time-series registration process, as necessary, to minimize gross differences between images that occur over the course of the contrast-agent enhancement.

3.2. Semi-Automatic Contour Registration

The semi-automatic contour method of registering the 2D time series is accomplished by minimizing a cost function based on the gradient magnitude of the intensities corresponding to the position of a user-traced contour of the kidney boundary. The first slice in the sequence is the template (base image) to which all subsequent slices are registered. Using MIPAV's polygon ROI (region of interest) user interface, the boundary of the kidney is traced on the first slice by the operator. This boundary is then evolved to the edge of the kidney using a 2D spline active contour. The resulting boundary is used as the model contour, which gets iteratively transformed while maximizing the sum (or minimizing the negative sum) of the gradient magnitudes of the match image at the contour's position. This method assumes that the kidney is a rigid body, and thus does not take into account out-of-plane motion. The algorithm must be performed separately for the left and right kidneys, as their displacements are not interdependent.

3.3. AIR Registration Adaptation

The following steps were taken to register the 3D time-series MR renography. The registration method was implemented with MEDx (Sensor Systems, Sterling, VA).

1. *Cropping.* A point at the center of a given kidney was identified manually. All images in the time series were cropped to a region of 100x100 pixels centered at that point. Cropping of the image is necessary to minimize non-rigid motion between time frames.

2. *In-plane Registration.* A region of interest (ROI) was drawn manually about the kidney in the first time frame at a slice in the center of the kidney. The ROI was superimposed on the corresponding slice in all subsequent time frames. The ROI was manually shifted to best match kidney location in each of those time frames. All images for each time frame are shifted by the equal and opposite shift that was manually applied to the ROI for that time frame.

3. *AIR Registration.* Each time-frame volume was registered with AIR v3.0. (6 parameter model, least-squares-intensity-correction cost function). Registration was performed in blocks of 3 time-frame volumes: the 1st, 2nd, and 3rd volumes were registered to the 0th volume. The 4th, 5th and 6th volumes were registered to the registered version of the 3rd volume *etc*.

4. Results

Time activity curves from the cortex from un-registered and registered images are shown in figure 2. A radiologist, blinded to the method of registration viewed movie sequences of a single slice extracted from MR renograms. The radiologist compared movies from sequences registered manually and with sequences registered by automated methods. The radiologist decided which, if either, registration method was superior. Results of comparison are summarized in tables 1 and 2. While the radiologist preferred the manual registration of the 2D renogram, in practice, the time necessary for complete manual registration of the 2D time-series is prohibitive (20 minutes for 140 images).

	Manual Registration	AIR Registration Adaptation	Equivalent
Subject 1 (normal kidney)		✔	
Subject 2 (normal kidney)		✔	
Subject 2 (diseased kidney)	✔		

Table 1. Evaluation of registration performance of 3D MR renography.

	Manual Registration	Landmark Registration	Equivalent
Subject 3	✔		

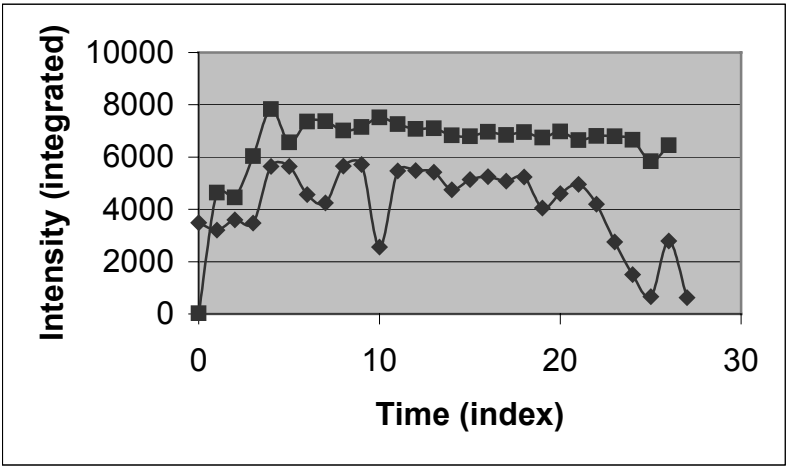Table 2. Evaluation of registration performance of 2D MR renography.

Figure 2. Time activity curves of renal cortex of 3D MR renogram. Time activity curves are shown from ROI drawn on the cortex of kidney (Subject 1). Unregistered time series are shown as diamonds and registered images are shown as squares.

5. Conclusions

We have found that automated 2D and 3D registration methods can equal or exceed the performance of manual registration of MR renography. Further work is needed to increase the degree of automation.

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